# Surface climatology data derived from three-year IASI measurements and initial evaluation

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### **Motivation**

Study Earth from space to improve our scientific understanding of global climate change; derive geophysical parameters of surface and atmosphere from satellite hyperspectral IR measurements.

- Long-term and large-scale observations, needed for global change monitoring and other research, can only be supplied by satellite remote sensing.
- IR hyperspectral radiance measurements are available from current AIRS (since May 2002) and IASI (October 2006), and CrIS will be available from future operational weather satellites.
- Generate an emissivity climatology dataset from satellite data in
  - 1) helping to understand the nature of radiative transfer process for the Earth and atmospheric environment,
  - 2) assisting assimilation of hyperspectral IR radiances in NWP models,
  - 3) improving retrieval accuracy for other thermodynamic parameters (e.g., T<sub>s</sub>, T, H<sub>2</sub>O, CO, CO<sub>2</sub>, O<sub>3</sub> ...),
  - 4) helping surface skin temp retrieval from other satellite broad-band measurements (e.g., GOES-R/ABI),
  - 5) improving accuracy of surface radiation budget calculation for climate studies, and
  - 6) long-term monitoring of the global environment and climate change.

### Hyperspectral Emis. Ret. Algorithms

- **C. C. Borel (1998):** Surface emissivity and temperature retrieval for a hyperspectral sensor, *Geoscience and Remote Sensing Symposium Proceedings*, 1, 546-549.
- **D. K. Zhou et al. (2002):** Thermodynamic product retrieval methodology for NAST-I and validation, *Appl. Opt.*, 41, 6957–6967.
- **R. O. Knuteson et al. (2004):** Infrared land surface remote sensing using high spectral resolution aircraft observations, *Advances In Space Research*, 33 1114–1119.
- **J. Li et al. (2007):** Physical retrieval of surface emissivity spectrum from hyperspectral infrared radiances, *Geophys. Res. Lett.*, 34, L16812.
- **L. Zhou et al. (2008):** Regression of surface spectral emissivity from hyperspectral instruments, *IEEE Trans. Geosci. Remote Sensing*, 46, 328–333.
- **J. Susskind et al. (2008):** Improved surface parameter retrievals using AIRS/AMSU data, *Proc. SPIE*, 6966, 10–12.
- **E. Péquignot et al. (2008):** Infrared Continental Surface Emissivity Spectra Retrieved from AIRS Hyperspectral Sensor, *J. Appl. Meteorol. Climatol.*, 47, 1619–1633.
- **X. Liu et al. (2009):** Retrieval of atmospheric profiles and cloud properties from IASI spectra using superchannels, *Atmos. Chem. Phys.*, 9, 9121–9142.
- **D. K. Zhou at al. (2011):** Global land surface emissivity retrieved from satellite ultraspectral IR measurements, submitted to *IEEE Trans. Geosci. Remote Sensing*.

#### And others I may miss....

### **IR-only Retrieval Algorithm**

#### Part A: Regression Retrieval (Zhou et al., GRL 2005)

Using an all-seasonal-globally representative training database to diagnose 0-2 cloud layers from training relative humidity profile:

A single cloud layer is inserted into the input training profile. Approximate lower level cloud using opaque cloud representation.

Use parameterization of balloon and aircraft cloud microphysical data base to specify cloud effective particle diameter and cloud optical depth:

Different cloud microphysical properties are simulated for same training profile using random number generator to specify visible cloud optical depth within a reasonable range. Different habitats can be specified (Hexagonal columns assumed here).

Use LBLRTM/DISORT "lookup table" to specify cloud radiative properties:

Spectral transmittance and reflectance for ice and liquid clouds interpolated from multi-dimensional lookup table based on DISORT multiple scattering calculations.

Compute EOFs and Regressions from clear, cloudy, and mixed radiance data base:

Regress cloud, surface properties & atmospheric profile parameters against radiance EOFs amplitudes.

#### Part B: 1-D Var. Variational Retrieval (Zhou et al., JAS 2007)

A one-dimensional (1-d) variational solution with the regularization algorithm is used for physical retrieval methodology which uses the regression solution as the initial guess.

Cloud optical and microphysical parameters, namely effective particle diameter and visible optical thickness are further refined with the radiances observed within the 10.4 to 12.5 µm window.



### Emissivity $(\varepsilon_{\nu})$ is linear to Radiance $(R_{\nu})$

$$\begin{split} R_{v} &= \varepsilon_{v} B_{v}(T_{s}) \tau_{v}(p_{s} \rightarrow 0, \theta_{sat}) + \int_{p_{s}}^{0} B_{v}[T(p)] \frac{d\tau_{v}(p \rightarrow 0, \theta_{sat})}{dp} dp \\ &+ F_{v}^{d} \rho_{v}^{t} \tau_{v}(p_{s} \rightarrow 0, \theta_{sat}) + \frac{H_{v}}{\sec(\theta_{sun})} \tau_{v}(0 \rightarrow p_{s}, \theta_{sun}) \rho_{v}^{s} \tau_{v}(p_{s} \rightarrow 0, \theta_{sat}) \\ &= [\int_{p_{s}}^{0} B_{v}[T(p)] \frac{d\tau_{v}(p \rightarrow 0, \theta_{sat})}{dp} dp + F_{v}^{d} \tau_{v}(p_{s} \rightarrow 0, \theta_{sat}) + \frac{H_{v}}{\sec(\theta_{sun})\pi} \tau_{v}(0 \rightarrow p_{s}, \theta_{sun}) \tau_{v}(p_{s} \rightarrow 0, \theta_{sat})] \\ &+ [B_{v}(T_{s})\tau_{v}(p_{s} \rightarrow 0, \theta_{sat}) - F_{v}^{d} \tau_{v}(p_{s} \rightarrow 0, \theta_{sat}) - \frac{H_{v}}{\sec(\theta_{sun})\pi} \tau_{v}(0 \rightarrow p_{s}, \theta_{sun}) \tau_{v}(p_{s} \rightarrow 0, \theta_{sat})] \varepsilon_{v} \\ &= k_{1} + k_{2} \varepsilon_{v} \end{split}$$

The surface is assumed to be Lambertian (or diffuse reflection):

 $\rho_{v}^{t}$  = spectral surface reflectivity,  $(1 - \varepsilon_{v})$ 

 $\rho_v^s$  = spectral solar reflectivity,  $(1-\varepsilon_v)/\pi$ 

 $R_{y}$  = observed spectral radiance

 $\varepsilon_v$  = spectral emissivity

 $B_{v}$  = spectral Planck function

 $T_s$  = surface skin temperature

 $\tau_{\nu}(p_1 \rightarrow p_2)$  = spectral transmittance from pres.  $p_1$  to  $p_2$ 

T(p) = temperature at pressure p

H =solar irradiance

 $\theta_{sun}$  = solar zenith angle

 $\theta_{sat}$  = sattlite zenith angle

 $F_v^d$  = down welling thermal flux

### **Training Dataset & Emissivity Regression**

**Atmospheric:** An all-seasonal-globally representative training database (UW SeeBor Database).

Surface:  $T_s = T_a + T_\delta$ , where  $T_\delta$  is a random number generated value with a mean of 0 K and a STD of 3

K over water and 10 K over land.  $\varepsilon$  is randomly assigned to profile from  $\varepsilon$  database.

Cloud: Use parameterization of balloon and aircraft cloud microphysical data base to specify cloud

effective particle size and cloud optical depth using random number generator to specify

visible cloud optical depth within a reasonable range.

$$F(\varepsilon_v) = \log[\log(\varepsilon^{\rm HB} - \varepsilon^{\rm LB} + \delta) - \log(\varepsilon^{\rm HB} - \varepsilon_v)]$$

 $F(\varepsilon_v) = \log[\log(\varepsilon^{HB} - \varepsilon^{LB} + \delta) - \log(\varepsilon^{HB} - \varepsilon_v)]$  • Lab. measured emis. converted to emis. logarithm function  $F(\varepsilon)$ to constrain emis. retrieval.

$$A_i^F = \sum_{j=1}^{nch} F_j(\varepsilon) \varphi_{ji}^F$$

 $A_i^F = \sum_{j=1}^{ncn} F_j(\varepsilon) \varphi_{ji}^F$  • A set of emis. logarithm functions are used to calculate its Eigenvectors and their amplitudes. Emis. amplitudes are used with other other parameters as a state vector to calculate radiance.

$$A_i = \sum_{j=1}^{nc} R_j \varphi_{ji}$$

 $A_i = \sum_{j=1}^{m} R_j \varphi_{ji}$  • A set of radiances are used to calculate its Eigenvectors and their amplitudes.

$$S_{j} = \sum_{i=1}^{n-1} K_{ji} A_{i} + K_{jn} P_{s} = \sum_{i=1}^{n-1} K_{ji} (\sum_{l=1}^{nc} R_{l} \varphi_{li}) + K_{jn} P_{s}$$

 $S_{j} = \sum_{i=1}^{n-1} K_{ji} A_{i} + K_{jn} P_{s} = \sum_{i=1}^{n-1} K_{ji} (\sum_{l=1}^{nc} R_{l} \varphi_{li}) + K_{jn} P_{s}$  • Regression coefficients are generated using a training database (state vector) and their associated radiances. State vector is retrieved with measured radiance. Functional emis. EOF amplitudes are part of the state vector.

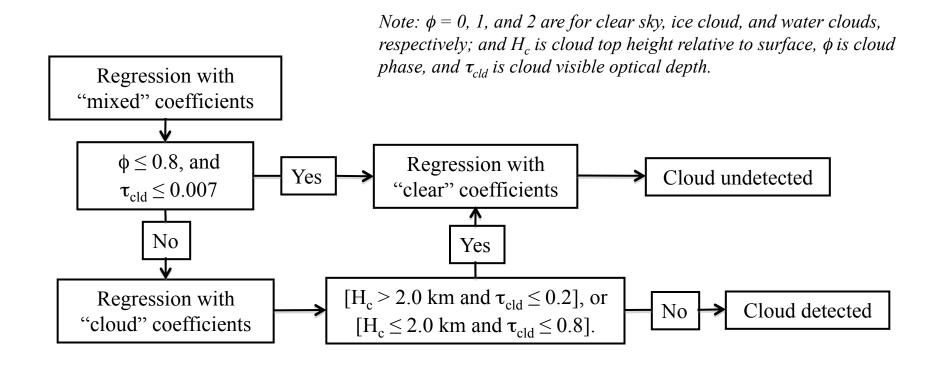
$$\varepsilon_{j} = \varepsilon^{\text{HB}} - \exp[\log(\varepsilon^{\text{HB}} - \varepsilon^{\text{LB}} + \delta) - \exp(F_{j})]$$

$$= \varepsilon^{\text{HB}} - \exp[\log(\varepsilon^{\text{HB}} - \varepsilon^{\text{LB}} + \delta) - \exp(\sum_{i=1}^{9} \varphi_{ji}^{F} A_{i}^{F})]$$

• Emissivity spectrum is calculated with retrieved emis. EOF amplitudes (i.e., functional emis. PC scores).

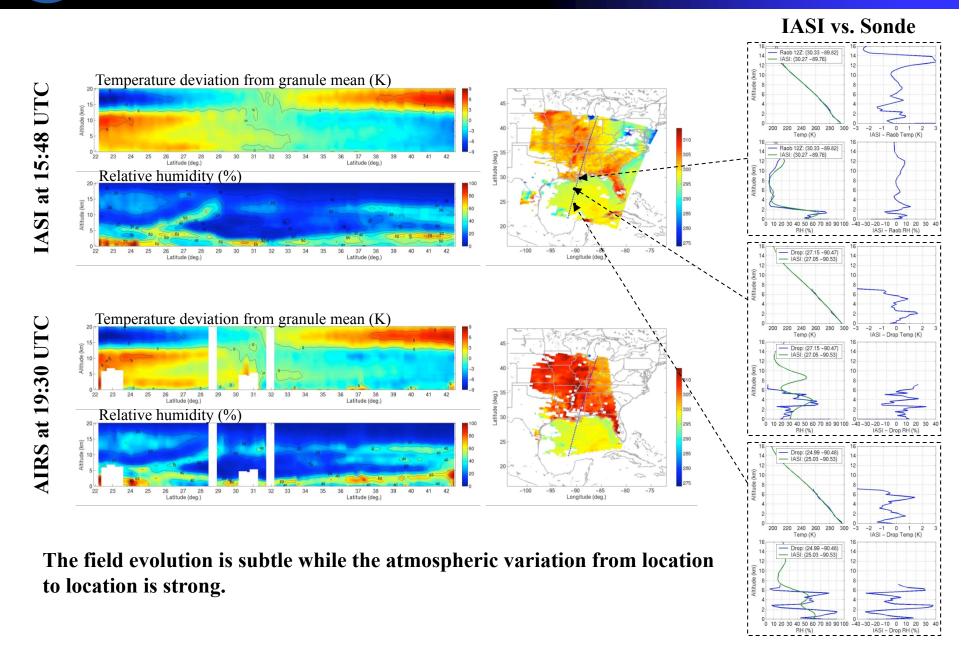
### **Cloud Detection within Retrieval**

Multi-stage regression retrievals are performed. The first-stage involves mixed (i.e., clear and cloudy) regression. The second-stage (e.g., either clear or cloudy) depends on the cloud detection criteria that are based on first-stage retrieved cloud parameters.



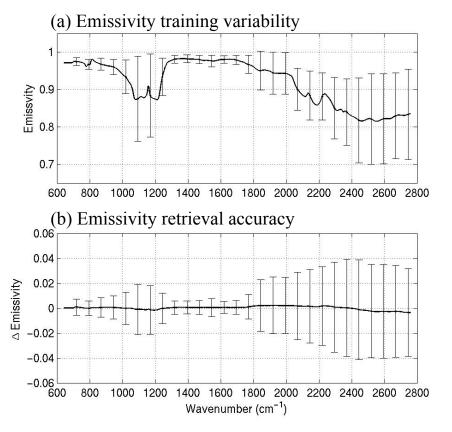


## APC paper: AIRS vs. IASI (4/29/2007)





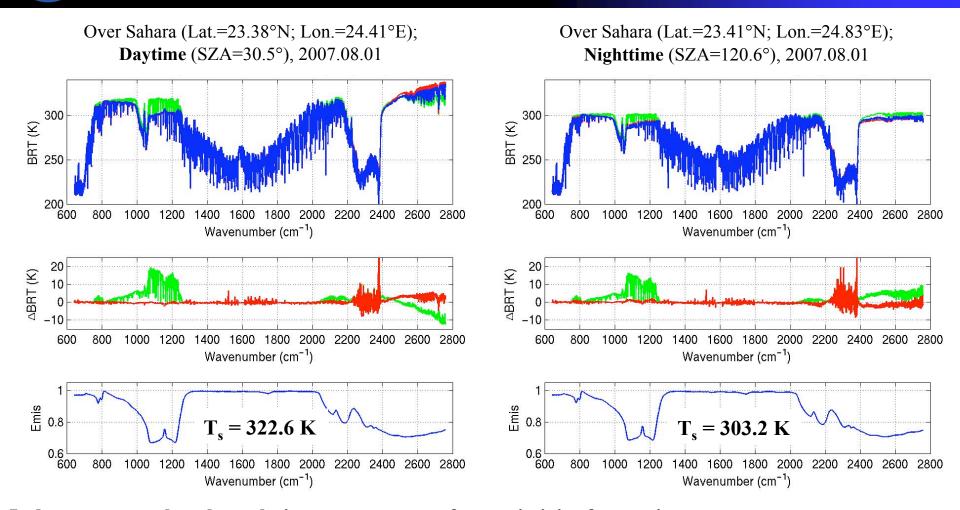
### **Emis. Accuracy Estimation Under Clear-sky**



- The emissivity assigned to each training profile is randomly selected from a laboratory measured emissivity database, indicated in panel **a**, and has a wide variety of surface types suitable for different geographical locations. The vertical bars show the emissivity STD for this dataset.
- Estimated surface emissivity retrieval accuracy, the mean difference (or bias) in curve and the STDE in vertical bars shown in panel **b**, is training data dependent.
- Surface skin temperature is one of the most "coupled" parameters with emissivity, it is necessary to mention that skin temperature retrieval accuracy has a -0.035 K bias with a 1.11 K STDE from the same analysis

Note: since the emissivity is linear to channel radiances, we chose to use retrieved emissivity from linear EOF regression, not further retrieved in physical iteration. However, if the physical retrieval is performed for other parameters, emissivity will be further refined through physical iteration.

### **Emis. Ret. and Rad. Fitting Samples**



#### It demonstrates that the technique separates surface emissivity from skin temperature:

Samples shown are for both day and night observations over the Sahara Desert. Simulated spectral radiances (with rtv emis in red curves; emis of 1 in green curves) are plotted in comparison with the measurements (blue curves). Retrieved surface emissivity spectra are plotted in the bottom panels with IASI day and night observations, respectively.



### Namib and Kalahari Deserts for Validation

Namib: Lat.= 26.35 S, Lon.=20.7 E



**Kalahari:** Lat.= 24.75 S, Lon.=15.3 E







### Namib and Kalahari Deserts for & Validation

- G. C. Hulley, S. J. Hook, E. Manning, S.-Y. Lee, and E. Fetzer, "Validation of the Atmospheric Infrared Sounder (AIRS) version 5 land surface emissivity product over Namib and Kalahari deserts," *J. Geophys. Res.*, vol. 114, no. D1, pp. 9104.1–9104.11, Oct. 2009.
- **Kalahari:** The majority of the sand lies on the level plains of the Kalahari Basin, sand dunes mixed with grassy scrublands and sparse trees.
- Namib: The vast expanse of shifting dunes is almost completely devoid of vegetation except for sparse perennial grasses.
- Different sand mineralogy from Namib to Kalahari sites.

**Table 1.** Summary of the Major Characteristics of the Kalahari and Namib Validation Sites Including Locality, Elevation, Surface Area, Dune Height, Grain Size, Sand Source and Bulk Mineralogy

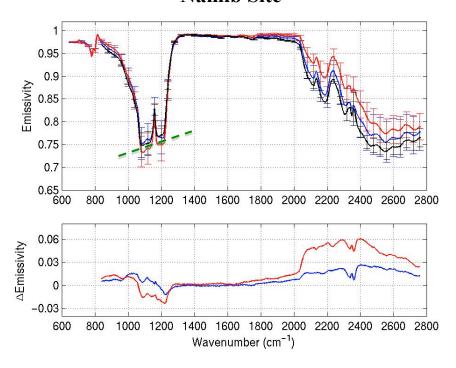
	Kalahari	Namib
Locality	covers most	western coast
	of Botswana,	of Namibia
	including northwestern	
	South Africa and	
	southeastern Namibia	
Approximate surface area (km²)	100,000	34,000
Elevation (m)	1,000	0 - 500
Maximum dune	30	300
height (m)		
Percent of grain size of sand		
$>$ 500 $\mu \mathrm{m}$	0%	1%
$250-500 \ \mu \text{m}$	30%	53%
$125-250 \ \mu m$	68%	40%
$<$ 125 $\mu$ m	2%	6%
Sand source	aeolian deposited,	littoral, fluvial,
	fluvial	weathered
		tsondab sandstone
Mineralogy		
Major	Quartz	quartz
Minor		feldspar,
		magnetite



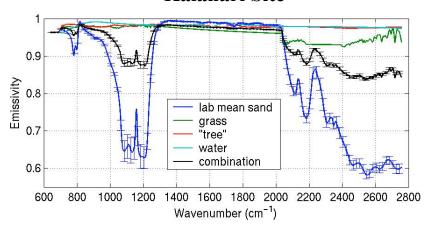
### **Emissivity Validation / Evaluation**

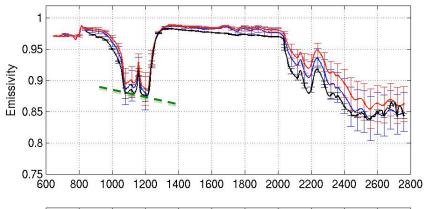
- We will use the Namib site for absolute validation and the Kalahari site for relative spectral-shape validation.
- The quartz-doublet region from the Namib to the Kalahari site, is well captured by retrievals, due to the different sand mineralogy at these 2 sites.

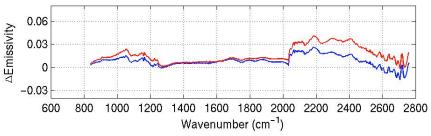
#### **Namib Site**



#### Kalahari Site







### "Quality" Filter for Global Assembled Mean

#### Cloud filtering and "outlier" rejection:

- Due to cloud coverage, not every measurement can provide surface parameters; however, the surface parameters can be retrieved under optically thin clouds with a relatively poor accuracy in comparison with that retrieved under clear-sky conditions.
- The surface emissivity composition can be assembled over a period of time and area. Single retrievals within a spatial grid (area) meeting the Quality Filter criteria will be taken to generate a mean emissivity.

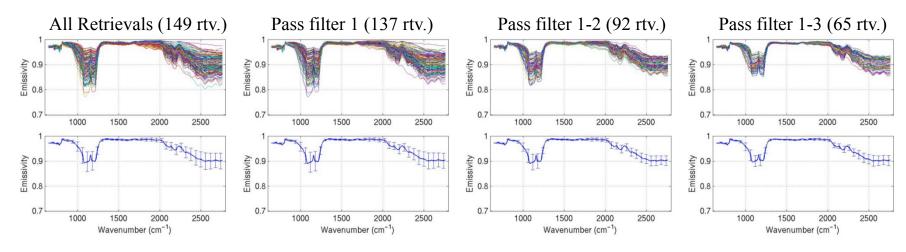
"O. F." criteria are listed as:

1. 
$$\tau_{cld} \leq 0.5$$
,

2. 
$$\left| A_1^F - \overline{A_1^F} \right| \le std(A_1^F)$$
, and  
3.  $\left| A_2^F - \overline{A_2^F} \right| \le std(A_2^F)$ .

$$3. \left| A_2^F - \overline{A_2^F} \right| \le std(A_2^F).$$

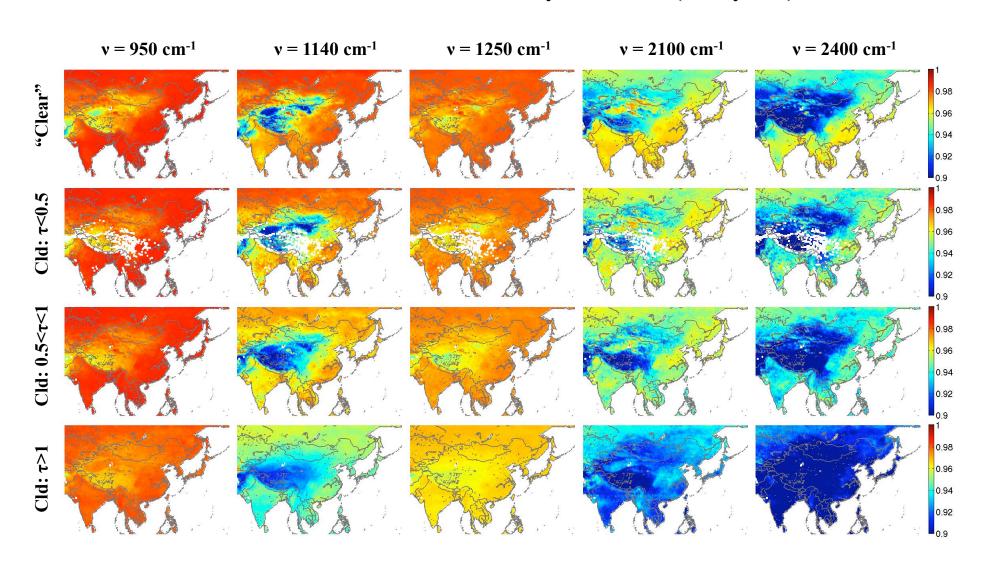
#### April 2009 – Rub' al Khali, Saudi Arabia [21.25° < lat. ≤ 21.75°; 54.25° < lon. ≤ 54.75°]





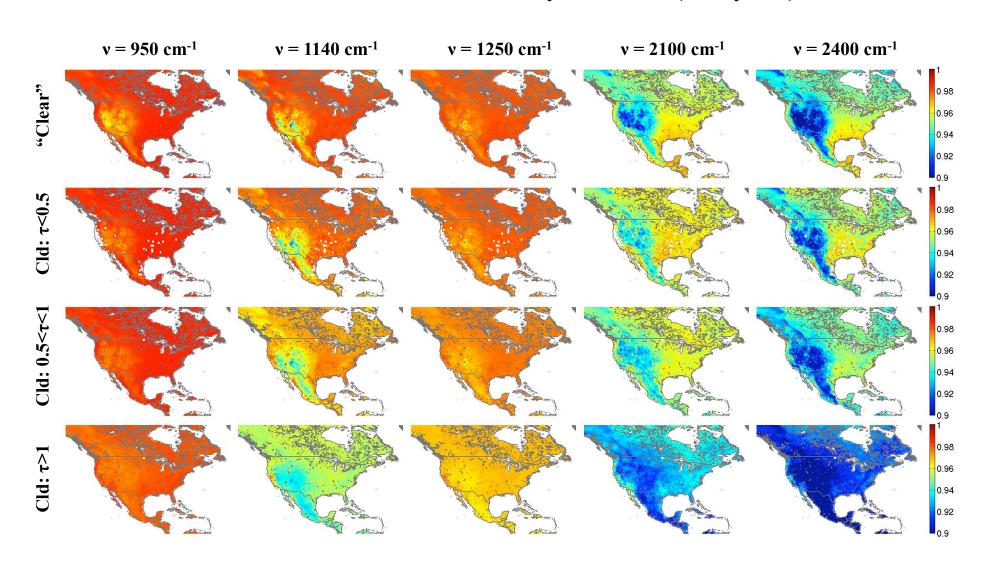
### Cloud Effects on Retrievals: Asia - China

#### Data used: IASI measurements July 2007-2010 (four-years)



### Cloud Effects on Retrievals: N. America – USA

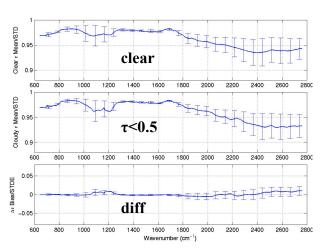
#### Data used: IASI measurements July 2007-2010 (four-years)

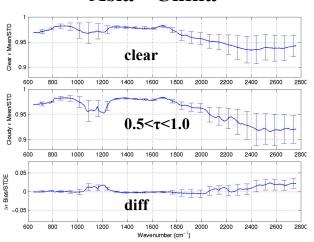


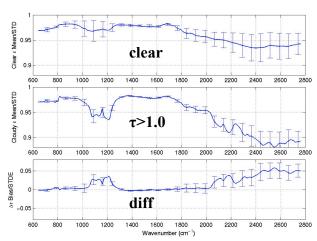


### **Regional Statistics**

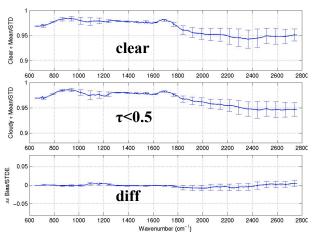
#### Asia - China

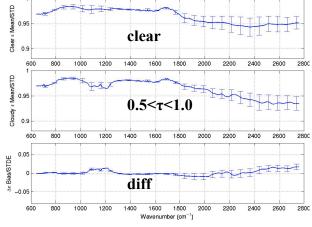


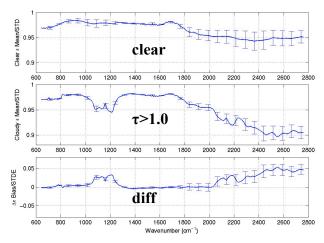




#### **North America - US**







### IR Surface Emissivity Climatology Datasets

Based on three-years IASI measurements (June 2007 – May 2010).

Land Surface Emissivity: 5-D (Emis., Lat., Long., Spectral frequency, and Time) Land Surface Skin Temperature: 4-D (Temp., Lat., Long., and Time)

Spatial resolution: 0.5x0.5 deg. Lat.-Long. (360x720=259200 grids)

Temporal resolution: weekly (52 weeks).

Spectral resolution: 0.25 cm<sup>-1</sup> from 645 to 2700 cm<sup>-1</sup> (every IASI spectral channels: 8461).

**Emissivity value** 

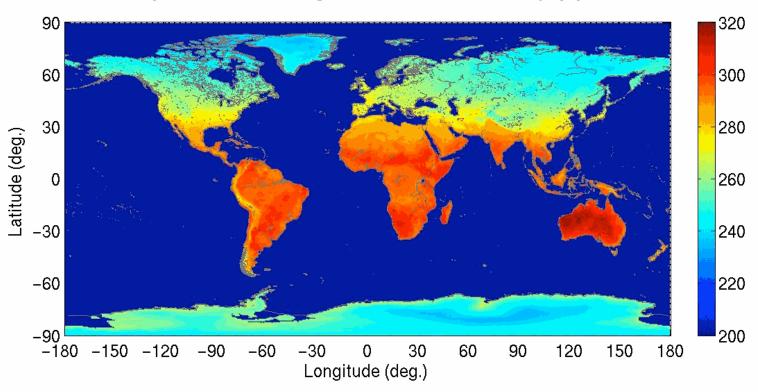
(or surface skin temp.)

The datasets also can be separated between daytime (descending mode) and nighttime (ascending mode)



### **IASI Derived 4-D LST (Temporal)**

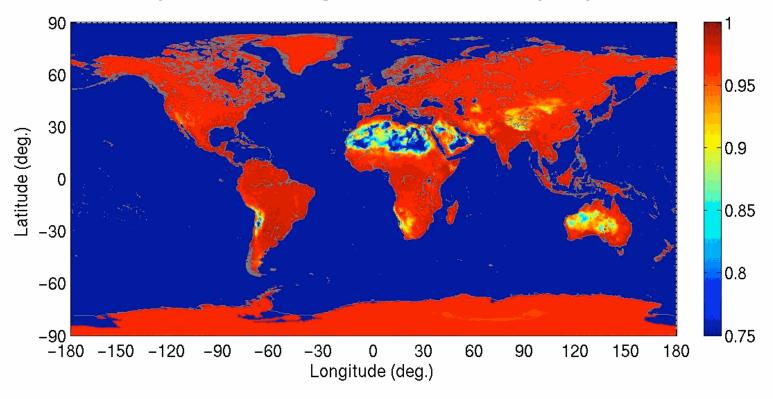
#### 01 Weekly Mean at 0.5-deg. Scale: Land Surf Temp (K)





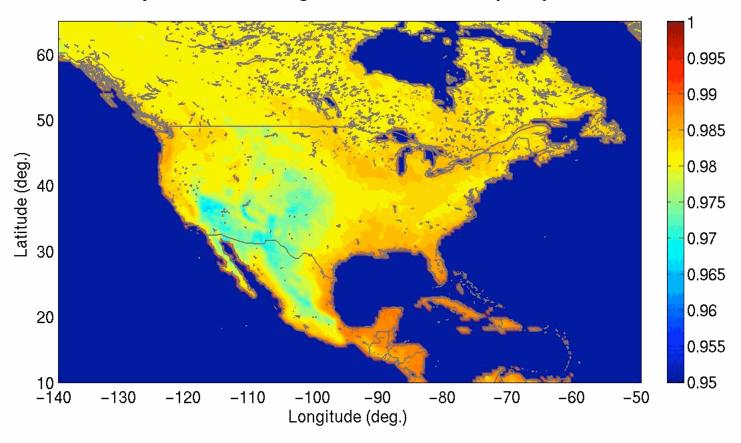
### **IASI Derived 5-D LSE (temporal)**

#### 01 Weekly Mean at 0.5-deg. Scale: Emis at 1140 (1/cm)



The emissivity variation is coherent, which indicates that the emissivity variation is associated with seasonal changes of the weather or surface weather (i.e., rainfall modifying soil moisture or snowfall accumulating on the surface) and the varying ground cover with a different vegetation coverage.

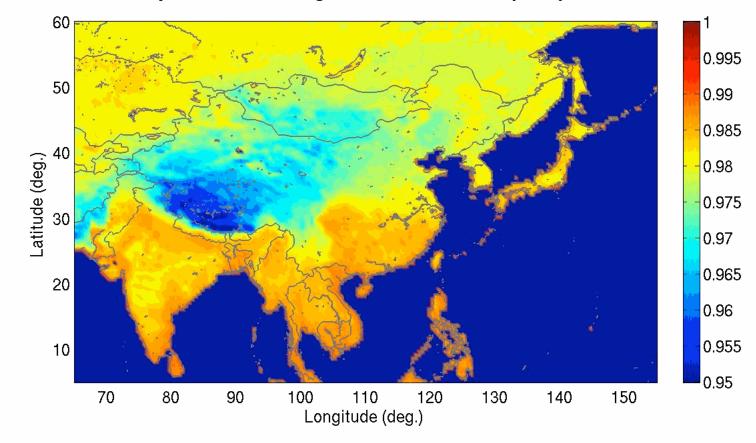
#### 01 Weekly Mean at 0.5-deg. Scale: Emis at 950 (1/cm)



### LSE Seasonal Variation (950 cm<sup>-1</sup>): Asia

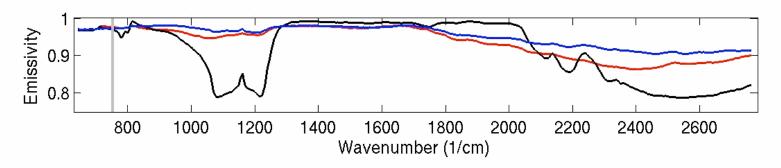
Each spring after a cold, sunny, windy, and dry winter, sandstorms strike Northern China and the yellow dust migrates from China's interior (the Gobi and Ordos deserts) to its capital, Beijing, and eastern seaboard, thus decreasing the emissivity over wide regions while the ground is still very dry with minimum rainfall in the winter and early spring seasons.

#### 01 Weekly Mean at 0.5-deg. Scale: Emis at 950 (1/cm)

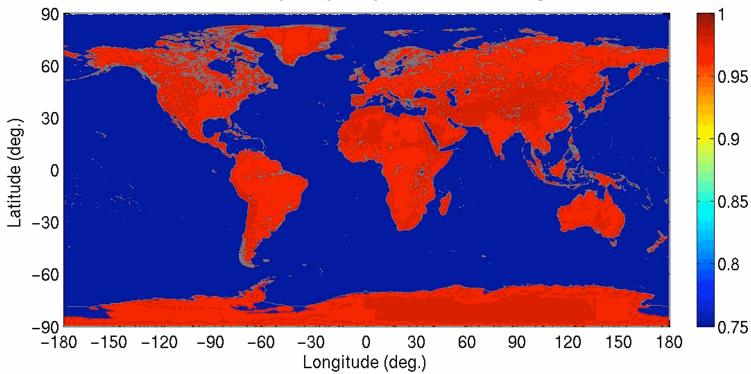




### **IASI Derived 5-D LSE (Spectral)**

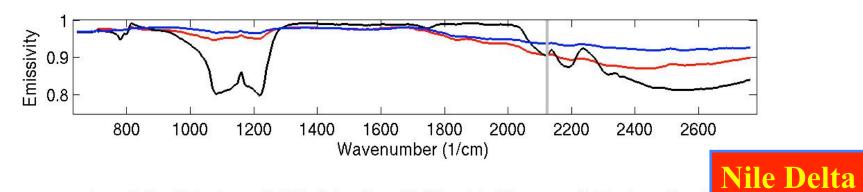


#### Land Surf Emis at 750 (1/cm); July Mean at 0.5-deg. Scale

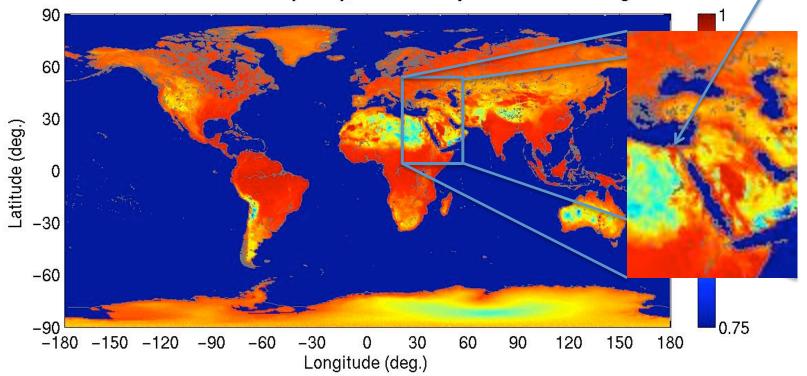




### **IASI Derived 5-D LSE (Spectral)**







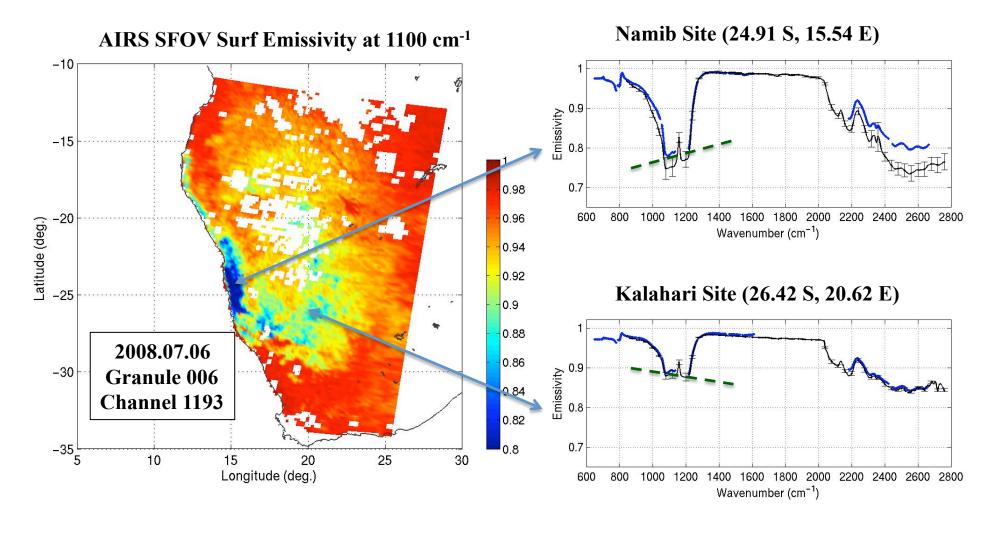
### **How about AIRS?**

Can we derive similar emissivity spectra from AIRS measurements?

YES!

### **AIRS Emissivity Retrieval Samples**

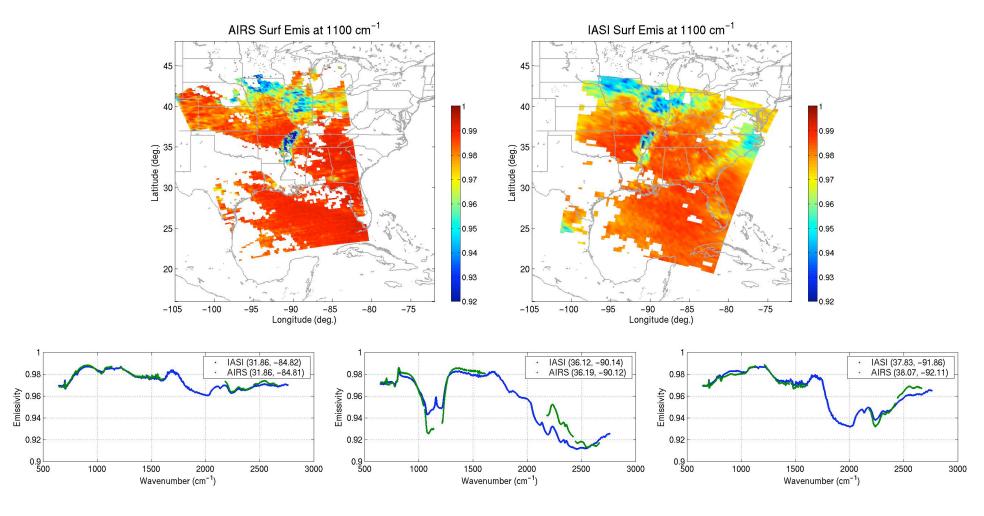
AIRS SFOV retrieval from 2008.07.06 Granule 001 (Emissivity map from AIRS Channel 1193). retrievals compares with the mean laboratory result for the Namib and Kalahari sites, respectively. In the quartz doublet region between 1000 and 1200 cm<sup>-1</sup>, the emissivity spectra shape compares well with laboratory results and IASI results.





### AIRS vs. IASI Emissivity

AIRS and IASI SFOV emissivity retrieval intercomparison from JAIVEx case (April 29, 2007). Intercomparison of emissivity map at 1100 cm<sup>-1</sup> shows that the agreement between the AIRS and IASI (longwave region) is within at ~0.01 or less. Few point-to-point sample inter-comparison of spectral emissivity are plotted showing different land surface spectral emissivity captured by both AIRS and IASI.



### Summary

- A state-of-the-art retrieval algorithm, dealing with all-weather conditions, has been developed and applied to IASI radiance measurements. Surface emissivity is retrieved using multi-stage linear EOF physical-regressions.
- Initial emissivity validation over the Namib and Kalahari deserts is performed. IASI Emissivity retrieval accuracy under clear-sky conditions is estimated that a STDE is about 0.02 and 0.04 for longwave and shortwave window regions, respectively.
- Results from IASI retrievals indicate that surface emissivity retrieved with satellite IR ultraspectral data can capture different land surface type properties. The seasonal variation of global land surface emissivity derived from satellite IR ultraspectral data is evident.
- Land surface emissivity data retrieved under clear and cloudy conditions are used to evaluate emissivity retrieval accuracy affected by the cloudy with different cloudy categories. IR hyperspectral sounder (e.g., IASI) can provide good retrievals under the optically thin clouds with a cloud effective optical depth less then 0.5.
- We have initially developed an IR emissivity climatology database from three-years IASI measurements.
- Initial retrievals from AIRS data using the same retrieval technique is promising, showing expected emissivity spectral and spatial variations.